Deep Learning for Drought Damage Prediction Using Smartphone Images of Crops

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Abstract

Smallholder farmers need to work hard to ensure their financial security, yet natural crop damage threatens to destabilize that security. Current processes for insurance claims on damaged crops exist, but are slow. This project aims to improve the insurance claims settlement process for smallholder farmers in Africa by utilizing convolutional neural networks. With a focus on creating a precise and effective predictive model designed for assessing drought damage, this project makes use of a dataset comprising historical smartphone images provided by smallholder farmers spanning various agricultural seasons. Key objectives involve the development of a convolutional neural network and investigating the potential benefit of heuristics to the predictive capability of such a model.

Code for this project is available at: https://github.com/andreasnaoum/drought-damage-prediction/

Contents

List of Acronyms and Abbreviations

IFPRI	International Food Policy Research Institute
ACRE	Agriculture and Climate Risk Enterprise
CGIAR	Consultative Group on International Agricultural Research
ML	Machine Learning
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error

1 Introduction

The agricultural landscape in Africa faces a number of challenges, and among them, the vulnerability of smallholder farmers to the impacts of climate change poses a significant threat to food security and economic stability [1]. In this context, efficient and equitable crop insurance processes play a crucial role in mitigating risks and safeguarding the livelihoods of smallholder farmers.

1.1 Literature Review

Artificial intelligence is rapidly gaining traction in the insurance industry, showing great promise across various applications such as specific insurance tasks, claim prediction, fraud detection, and more [2]. Our proposed solution, focusing on predicting crop damage through smartphone images, aligns with the broader trend of researchers developing models for various scenarios using images or other data (e.g. IoT, UaV images) to forecast damage and claims [3, 4, 5, 6, 7]. This underscores the expansive potential of AI in predictive analytics across diverse domains within the insurance sector.

Deep Learning emerges as a suitable tool for tackling specific insurance tasks, particularly those involving image analysis. Specifically, it has the capacity to recognise patterns and features within images, enabling precise assessments in such scenarios. A striking example is evident in its application to classify vehicle damage as no, medium, or huge damage for image-based vehicle insurance. In addition, this model can detect if an image is a screenshot or a picture from the screen to prevent fraud [6]. Deep Learning is a valuable asset in the evolving landscape of insurance technology.

While artificial intelligence holds immense potential in reshaping insurance practices[2], the practical adoption, as seen in the context of ACRE Africa, is still in a transitional phase and involves extensive data collection. Currently, ACRE Africa employs manual assessment of smartphone images submitted by insured farmers to determine the extent of drought-related crop damage, a labour-intensive and time-consuming task [8]. These methods of assessing crop damage are prone to delays and faults. However, they started collecting data and transitioning to automated processes using artificial intelligence. This operational reality highlights a critical challenge within the industry that our proposed solution aims to support.

Regarding the beginning of digital transformation in crop insurance, Ceballos and Kramer [1] proposed the integration of digital technologies into crop insurance in India, comparing traditional index-based insurance with the PBI. In contrast to proxy measures, PBI directly ties insurance payouts to individual crop losses, resembling traditional indemnity insurance. However, this approach reintroduces information asymmetry challenges, including moral hazard and adverse selection, which could potentially compromise the sustainability of the product. The study addresses adverse selection at both the farmer and plot levels, exploring if riskier farmers are willing to pay more for insurance coverage and if selected plots exhibit riskier characteristics.

PBI is a novel concept involving farmers capturing smartphone images of their plots throughout the growing season to document crop development and damage [1]. These images are then uploaded to a server, where experts analyze the time-lapse data to estimate the percentage of crop damage. The analysis also reveals that farmers perceive PBI insurance as a valuable complement, and the demand for PBI is not crowded out when adhering to picture-taking protocols. The study emphasizes that PBI has the potential to enhance demand and engagement.

In a related study, Ceballos et al.[9] investigated the use of PBI specifically within the context of smallholder farmers in India. The article emphasizes the technical feasibility of PBI and its capacity to reduce basis risk, enhancing trust in index-based insurance for smallholder farmers. The study conducted in wheat-growing regions with high smartphone penetration among farmers demonstrates that PBI effectively assesses severe crop losses, reducing downside basis risk compared to conventional index-based insurance products. Furthermore, the article suggests the potential of PBI to complement existing satellite-based damage estimation methods and facilitate fail-safe indices or gap insurance. Overall, these studies collectively highlight the feasibility and value of PBI in improving insurance claims settlement for smallholder farmers.

Moreover, Waithaka L. et al. [10] stands out for its innovative approach to mitigating basis risk in crop insurance processes. The development of a hybrid picture-based insurance (PBI) product, integrating weather index-based insurance (WBI) for rating and pricing alongside picture-based monitoring for visible crop damage coverage, addresses challenges associated with delays in claims settlement. The introduction of deep learning models for automated drought prediction has demonstrated impressive accuracy, with growth stage classification at 75%, visible drought classification at 89%, and extent of drought predictions at 86%.

The "Eyes on the Ground" project is the foundation of ML applications to automate claims settlement and achieve predictive accuracy. This project arises from the collaboration between ACRE Africa, the IFPRI, and the Lacuna Fund, and its goal is to create an open-source large dataset to support the development of AI for agriculture. A valuable asset in this project is a dataset[11] consisting of historical smartphone images of crops in Africa collected over multiple agricultural seasons and contributed by smallholder farmers. While the project has successfully trained models for predicting drought damage over two seasons [10], the challenge lies in the transferability of these models to a third season where relevant data is available, but no models have been able to classify drought damage with this data yet accurately. Recognizing this challenge, the project has initiated a competition on Zindi [8], a platform dedicated to data science projects, to encourage innovative solutions in overcoming this transferability problem.

Notably, there is a gap in current studies about using PBI for developing predictive models using smartphone images by utilising ML techniques. While existing research explores the technical aspects and benefits of PBI, a dedicated investigation into the design and development of such models, including considerations like the structure of CNN and the potential use of heuristics, remains absent. This gap could be because insurance companies and organisations develop their ML models privately and limit shared knowledge within the research community.

Automating the insurance processes through ML models using historical smartphone images and ensuring the quality and transferability of such models is crucial for timely and fair compensation, and there is a potential for optimising the delivery of insurance services to the region's smallholder farmers.

ANNs constitute a family of models inspired by the intricate organization of the human brain. Comprising interconnected neurons structured in layers, ANNs, including feed-forward networks, utilize weighted sums and activation functions to capture diverse nonlinear relationships [12]. An example of a Neural Network with two hidden layers and multiple outputs is presented in Figure 1.

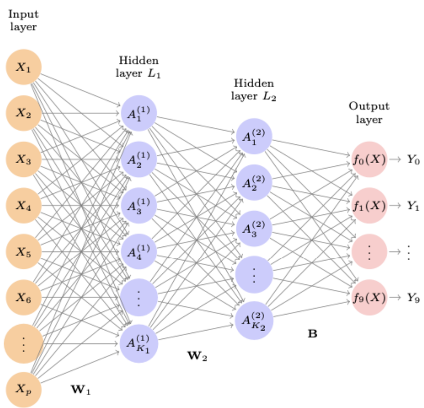


Figure 1: Neural network diagram with two hidden layers and multiple outputs. Source: [12]

CNNs, a specialised subset within the ANNs category, excel particularly in image classification tasks. Emulating human visual recognition, CNNs identify low-level features such as edges and colours, progressively integrating them to recognise higher-level features like eyes or ears. The fundamental components of CNN design are filters (see Figure 2 for an example), which function inside the convolution layers and are also referred to as convolutional kernels. These filters are essential for identifying unique patterns and characteristics, which helps the network efficiently classify visual data. The max-pooling layer (see Figure 3), which further improves the network's capacity to identify and prioritise important spatial information, is another crucial component of CNNs [12].

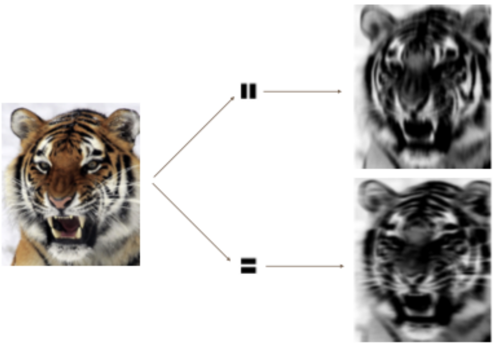


Figure 2: Convolution filters find local features in an image, such as edges and small shapes. Source: [12]

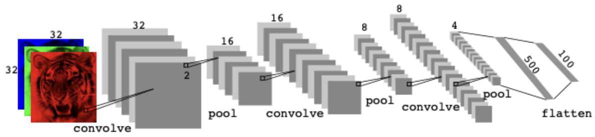


Figure 3: Architecture of a deep CNN. Convolution layers are interspersed with 2×2 max-pool layers, which reduce the size by a factor of 2 in both dimensions. Source: [12]

A method for accelerating machine learning algorithms is the use of heuristics [13]. In this context, heuristics form prior beliefs of data by connecting values to specific states ahead of time to save computational time and space [14]. They narrow down the state space by focusing on the most promising aspects. Cheng et al. [13] have shown the benefits of heuristics to the learning efficiency of reinforcement learning algorithms. Though they have yet to show this to work for CNNs specifically, this relation will be explored in this paper.

1.2 Research Questions and Objectives

This project aims to support the automation of crop insurance processes, specifically the drought damage assessment, using the dataset from the ”Eyes on the Ground” project and utilising ML. This research will help to uphold the economic viability of smallholder farmers in Africa by providing them with a fast and fair means to make insurance claims on their crops.

The primary goal of this research project is to create a predictive model for assessing drought damage from smartphone images, focusing on exploring heuristics and successfully transferring across multiple agricultural seasons. The central inquiry guiding this initiative involves understanding how ML techniques can be effectively employed to predict and assess drought-related crop damage from smartphone images and if a heuristic can be adapted to support the assessment.

1.3 Hypotheses

We proposed that utilizing machine learning techniques, specifically a CNN model, to analyze historical smartphone images from smallholder farmers in Africa will result in the development of a predictive model capable of accurately assessing drought-related crop damage. The model for drought damage assessment can be used to validate or invalidate the hypothesis.

Additionally, we hypothesize that a basic data analysis involving the extraction of a heuristic for the initial version of the model can provide valuable insights. Our first hypothesis posits that counting the number of dark pixels in an image will serve as a reasonably effective heuristic. The rationale behind this assumption is that darker colours may indicate cracked earth, a common manifestation of drought-related crop damage. Other heuristics will be explored. A heuristic can be instrumental in informing the development of the predictive model for assessing drought impact on crops. Subsequent testing and refinement will be undertaken to validate the efficacy of each suggested heuristic in the model.

2 Methods

In pursuit of developing an efficient and accurate drought damage assessment model, we employed a multifaceted methodological approach. Drawing upon the rich dataset of historical smartphone images contributed by farmers, our methodology includes data analysis and preprocessing, CNN design and development, heuristic exploration, and a final model that integrates CNN with the heuristic approach. This section provides a detailed insight into the data manipulation and the comprehensive research methodology employed to achieve the project's objectives.

2.1 Data Sources and Participants

For this research project, all data has been provided by the ”Eyes on the Ground” Challenge. This data consists of 26068 labelled training images and 8663 testing images. Adding other data sources to this project was considered, yet it was concluded that the provided dataset was to be used exclusively. This is firstly due to the sufficient size of the dataset for the purpose of this research project. Secondly, the potential difference in evaluation with other datasets would have led to unnecessary difficulty in merging results and, as such, would have been outside this project's scope. The images in the provided dataset were captured by farmers making insurance claims. As such, these farmers are indirect participants in this project.

Another data source was, however, used to analyze potential heuristics for drought classification. The participants in this data collection were seven acquaintances of the researchers.

2.2 Data Analysis and Preprocessing

In this section, we conducted an analysis of the data to extract valuable insights. Various preprocessing techniques were applied to ensure data quality and consistency. The refined dataset is then employed to train the ML model.

2.2.1 Data Analysis

The training data comprises images, each associated with attributes such as season, growth stage, damage, and extent. Descriptions of these variables are provided in Table 1. It is noteworthy that the test data only includes images without information on season, growth stage, and damage. The objective of this project is to predict the extent variable for this set. Here, the extent is the percentage of the severity of the given damage type in increments of 10%.

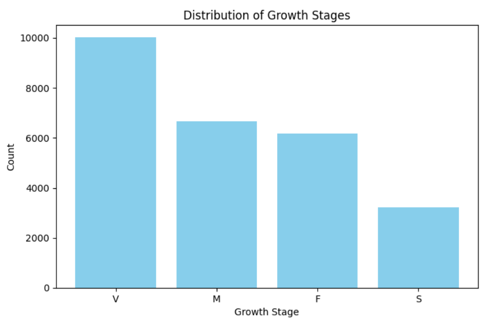


Figure 4: Distribution of Growth Stages

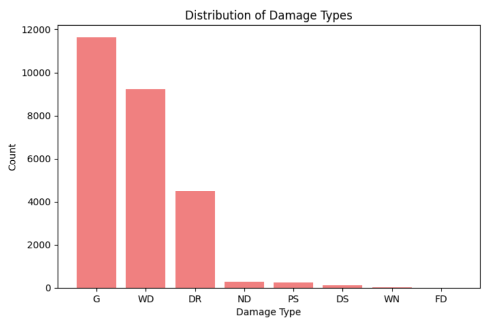


Figure 5: Distribution of Damage Types

At first, the dataset was thoroughly checked to ensure it met all the criteria for the desired modelling techniques. Following this initial assessment, the data was analyzed to gain a deeper understanding through visualization. The graphs in Figures 4, 5, 6, 7, 8, present key insights obtained during the exploratory data analysis.

The graph in Figure 4 illustrates the distribution of growth stages. It reveals a slightly higher frequency of 'Vegetative' (V) compared to other stages; however, it is a balanced overall distribution. Examining

Table 1: Variable Descriptions

Variable	Dependent/Independent	Type	Expected Properties	Parameters
image	Independent	Image	Crop Image	-
season	Independent	Categorical	Crop Growth Season	SR/LR SR or LR followed by the year, where SR is short rain and LR is the long rain season
growth_stage	Dependent	Categorical	Phenological Growth Stage	S (Sowing), F (Flowering), V (Vegetative), M (Maturity), NA (Not Classified)
damage	Dependent	Categorical	Crop damage	DR (Drought), WD (Weed), WN (Wind), DS (Disease), FD (Flooding), PS (Pest), ND (Nutrient Deficit), G (Good Growth), NA (Not Classified)
extent	Dependent	Numerical	The extent of the damage	0-100, where 0 means no damage 100 means complete damage

the distribution of damage types in Figure 5 reveals a predominant occurrence of 'Good Growth' (G), 'Weed' (WD), and 'Drought' (DR), which significantly surpasses the frequency of other damage types. Continuing with the analysis, Figure 6 illustrates the distribution of seasons. Notably, Long Rain (LR) seasons contribute a smaller portion compared to Short Rain (SR) seasons. In the extent distribution analysis referring to Figure 7, we find that out of the total 26,068 samples, more than 20,000, constituting over 75%, exhibit zero extent of damage.

Exploratory data analysis has been conducted for seasons specifically, as these insights can help to reveal the factors affecting seasonal transferability. From Figure 8b, it can be seen that the fraction of drought-labeled images to good-labeled images is more significant in the year 2020 than in 2021, yet there do not seem to be evident differences between the seasons of the same year as far as drought-damage according to these graphs.

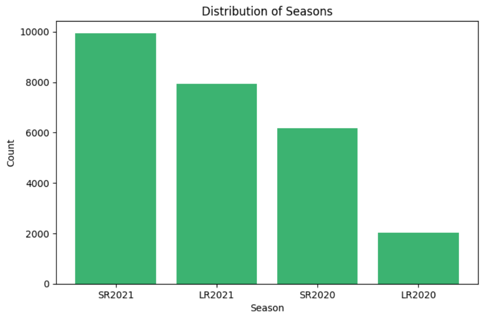


Figure 6: Distribution of Seasons

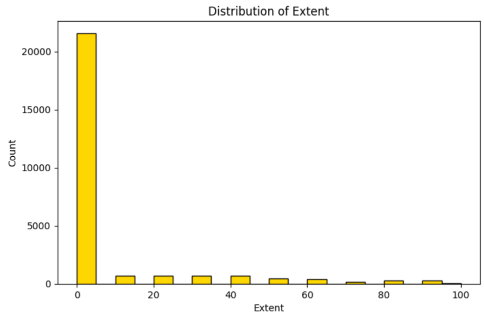
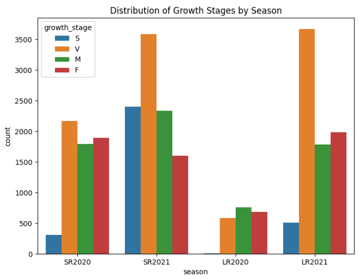
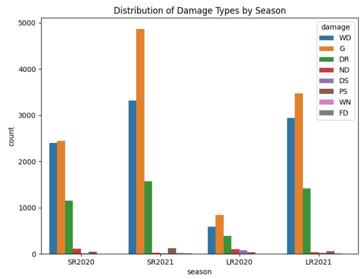


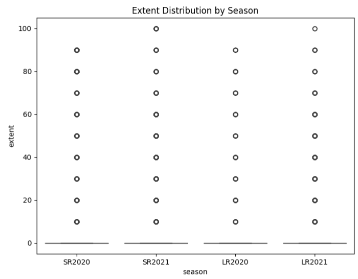
Figure 7: Distribution of Extent



(a) Growth Stages by Season



(b) Damage Types by Season



(c) Extent Distribution by Season

Figure 8: Exploratory Data Analysis for Seasons

2.2.2 Data Preprocessing

In the preprocessing pipeline, image resizing and padding techniques are utilized to ensure a consistent size across images (224x224 px), as raw images tend to differ in size. By setting up a constant size, training the CNN prevented loss of information around the borders of an image [12]. Additionally, the ”extent” column, representing drought damage, is normalized to values between 0 and 1. This normalization enhances the CNN’s effectiveness [12]. Lastly, the categorical data of the growth stage and damage type is transformed to a numerical value which the model can interpret and train on correctly.

2.2.3 Training, Validation and Test Sets

In total, the training data provided consists of around 26K images, with images distributed across seasons. A set comprising 20% of the training data was set aside to be used for model validation, and the remaining 80% was used for training. Finally, a dataset of around 8,5K images is used as the test set, and the model’s predictions are evaluated through the Zindi website by giving a public score for the error metric of the competition, the RMSE [8].

2.2.4 Network Architecture and Implementation

The (CNN) architecture used in this project draws inspiration from successful image processing tasks and is implemented using TensorFlow [12, 15]. TensorFlow is an open-source machine learning framework developed by the Google Brain team [16].

It initializes by accepting input images with dimensions of 224x224 pixels and three RGB colour channels. The initial convolutional layer employs 32 filters of size (3, 3), followed by a strategic max-pooling layer with a 2x2 window, effectively downsizing spatial dimensions. Recognizing the potential benefits of additional hidden layers, the current architecture includes two hidden layers with 64 and 128 filters, respectively, along with additional max-pooling layers. However, ongoing efforts involve exploration and evaluation of the most suitable configurations. The final layer is composed of a single neuron with linear activation, designed for predicting a continuous output within the range of 0.0 to 1.0. Finally, the raw output is multiplied by 100 and rounded to the nearest decade. This final value represents our prediction for the percentage of damage in the processed images. The architecture is visualized in Figure 9.

The network is trained using the Adam optimizer, mean squared error loss function, and MAE as a metric over a span of five epochs, leveraging a training generator and validating on a separate validation generator.

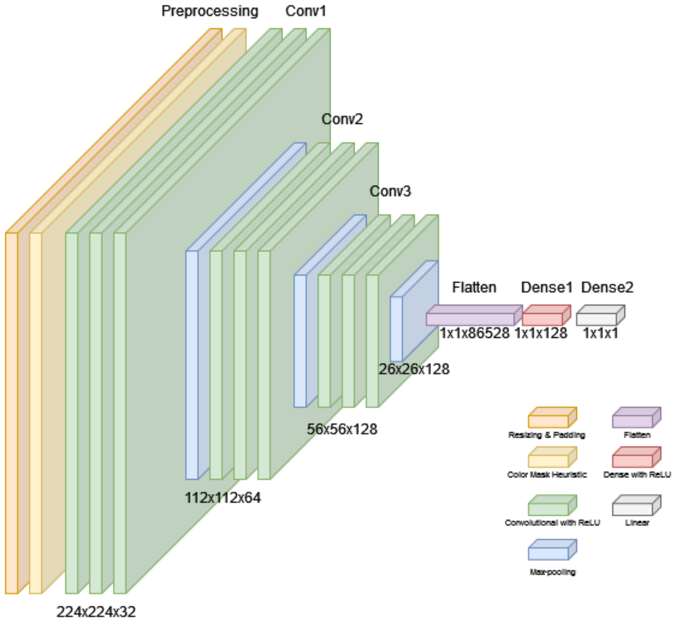


Figure 9: Architecture of the implemented CNN

2.2.5 Model Assessment

The metric chosen for the model evaluation in the competition is the RMSE [8, 17]. RMSE is a widely used metric for assessing the accuracy of predictive models. It quantifies the average magnitude of the errors between predicted and actual values, providing a comprehensive measure of the model's performance. Lower RMSE values indicate better model performance, with a value of 0 indicating perfect predictions. However, during the training of the model, MAE will be used, as RMSE is not available in the library used for evaluation. This discrepancy might lead to worse outcomes.

The RMSE is calculated by taking the square root of the mean of the squared differences between predicted ($\hat{y}$) and actual (y) values for each data point:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2} \tag{1}$$

where:

- N is the number of observations,
- $\hat{y}_i$ is the predicted value for the i-th data point,
- y_i is the actual (ground truth) value for the i-th data point.

In the context of our project, RMSE will serve as a crucial metric for evaluating the accuracy of our ML models in predicting drought damage levels from smartphone images.

2.3 Heuristic Exploration

This research was initiated by investigating a potential heuristic for identifying drought damage through image classification. Expecting the initial idea of counting the dark pixels, we set up a survey to explore other potential heuristics. The most promising heuristic will be implemented as a hybrid approach with the CNN model and compare the model accuracy with the simple CNN model.

2.3.1 Survey

The mentioned survey was set up in which a sample of 20 drought-damage-classified images from the training set were shown. Participants were asked to check which of the hypothesized heuristics were present for each of these images. They were also allowed to mention any other heuristic they believed to be present. The hypothesized heuristics were: "Brown Leaves, Yellow Leaves, Cracked Ground, Crooked / Fallen Plants". In total, this questionnaire received seven responses. In Table 2, the frequency of each of the heuristics is shown.

Heuristic	Occurrences (total 140)	Percentage
Brown Leaves	66	47.1%
Yellow Leaves	86	61.4%
Cracked Ground	7	5%
Crooked / Fallen Plants	32	22.9%
None of the Above	25	17.9%
Other	3	2.1%

Table 2: Table showing the number of occurrences and percentage of occurrence, out of 140 identification in the questionnaire, of each of the heuristics

These visualizations in Appendix A show that the variance of answers can significantly differ between images. For some images, such as number 18, there is explicit agreement on which attributes were present. There is no clear answer in other images, such as number 4. The accuracy of this method of identifying attributes is naturally susceptible to human errors and differences in interpretation. One method of getting more meaningful results is to increase the number of participants and the number of images in the survey. In this way, errors of interpretation are reduced. Otherwise, measuring high variance would allow us to draw a more accurate conclusion on the population.

One difficulty with the data is that some images are quite small and blurry, making it difficult to interpret them. One option is to remove these images from the survey. However, these low-quality images will still persist within the data, so we opted to leave them in with the hope that a way would be found to identify these images accurately regardless of their quality. The low-quality images in the survey were images 5, 6, 8, 10, 13, and 19. Out of these, images 6, 13, and 19 had a high variance of answers, images 5 and 10 were often answered with "None of the Above", and image 8 was answered relatively consistently.

Overall, the survey results indicated that most of the images we provided had semblances of brown or yellow leaves. These results will be taken into consideration when implementing the heuristic classification.

2.3.2 Hybrid Approach

In this project, a CNN is combined with a heuristic to enhance model predictions. The heuristic chosen for this study combines the two most prominent choices in the survey results, namely yellow and brown leaves. In order to detect these leaves in the dataset's images, it opted to utilize a colour mask which filters pixel colours in a range between two RGB values chosen to approximate the colours of yellow and brown leaves. This colour transformation was performed during the pre-processing stage of the training, after the resizing and padding of the images.

The colours picked for this heuristic have RGB values [205,133,63] and [255,255,224] for brown and yellow leaves, respectively. To re-emphasize, these colours approximate discoloured leaves, as true colour values vary due to factors such as lighting conditions and the type of crop being photographed. More accurate methods of detecting discolouration fall outside this study's scope. For this research, it suffices to work with a roughly estimated heuristic, as the primary goal is to determine whether using simple heuristics will increase the predictive capabilities of a CNN.

3 Results and Analysis

3.1 Model Training and Evaluation Metrics

Table 3: Training and Validation Metrics for Each Epoch

Model	Epoch	Loss	MAE	Validation Loss	Validation MAE
CNN	1	0.4949	0.1861	0.0395	0.1474
	2	0.0385	0.1489	0.0422	0.1497
	3	0.0380	0.1484	0.0409	0.1488
	4	0.0389	0.1510	0.0397	0.1485
	5	0.0372	0.1470	0.0367	0.1437
Hybrid Approach - Heuristic	1	0.8341	0.1485	0.0396	0.0811
	2	0.0284	0.0942	0.0311	0.1102
	3	0.0262	0.0896	0.0297	0.1155
	4	0.0250	0.0887	0.0308	0.0900
	5	0.0241	0.0872	0.0238	0.0925

The training process of the CNN model unfolded over five epochs, revealing a progressive reduction in both loss and MAE, indicating improved model performance. Notably, the validation metrics are closely aligned with the training metrics, suggesting the model's proficiency in generalizing to unseen data. These insights showed the effectiveness of the proposed methodology in addressing the research objectives. For the hybrid approach, the results seem similar to those of the CNN. Notably, the MAE for both the training and validation data are reduced by nearly half concerning the pure CNN model.

3.2 Analysis of Model Accuracy

Table 4: Rooted Mean Squared Error for Model

Model	RMSE
CNN	16.44817351
Hybrid Approach - Heuristic	15.69013985

The evaluation of the model on the dataset yielded a RMSE of 16.44817351, as measured on the Zindi platform. * This metric serves as a quantitative indicator of the model's predictive accuracy. The best performing solution, as of writing, is 6.677945689. Looking at the leaderboard, the paper's solution would rank in 87th place. The obtained result suggests that the model's predictions are not highly inaccurate, yet do leave room for improvement.

The hybrid approach led to a RMSE score of 15.69013985. This is an increase in accuracy of nearly 5% with this metric. From this, it can be concluded that the addition of a heuristic to the CNN model has had a positive influence on its predictive capabilities on the dataset used in this study.

* Competition leaderboard can be found here: `https://zindi.africa/competitions/cgiar-eyes-on-the-ground-challenge/leaderboard`

4 Discussion

4.1 Conclusion

From the results, it can be concluded that adding the heuristic to the CNN model has led to an accuracy of approximately 5% when predicting data from the Eyes on the ground dataset. This increase in accuracy has been measured with the RMSE metric through the Zindi platform [8]. The heuristic used in this study is a colour mask between approximate colour values for yellow and brown leaves. It was implemented during the pre-processing phase of the learning process and, as such, did not add to the complexity of the CNN model. From this study, it cannot be concluded that these results will generalize to any dataset or that the heuristics used were optimal, yet it provides a direction for exploring an additional asset to the machine learning toolbox, which will not necessarily cause models to become more complex.

4.2 Limitations of Study

The first limitation of this study to be addressed is the lack of diversity and depth of exploration of heuristics. For determining potential heuristics, a mere twenty images from the dataset were considered, which could arguably lead to a biased result for possible heuristics. Related to this, to detect yellow and brown leaves in images, the model is merely fed with colour-filtered images in this range. This is likely less accurate than setting up a separate model or augmenting the existing model for detecting discoloured leaves, though this would increase the complexity and training time of the model.

Besides the heuristical exploration and implementation, the study did not set the optimization of hyperparameters and model architecture as a priority. Instead, the study has focused on the comparison of predictive performance between a basic model, including and excluding a heuristic.

Lastly, the methods used in this study did not sufficiently aid in seasonal transferability, the ability for a model to detect crop damage regardless of season. From the data analysis performed on the seasonal data, a solution to this problem did not become apparent, and as such, this target was abandoned in light of the scope and time restraints of this research project.

4.3 Future Work

A major problem to be tackled in this study was the seasonal transferability of the model. In the end, the chosen methods did not result in an effective solution for this problem. To better tackle this problem, some suggested extensions are provided. Firstly, a rigorous data analysis is needed to discover potential factors for drought in each season. These factors have not been discovered from the data analysis in this study. Furthermore, it is possible that the data itself did not suffice for this discovery; therefore, another extension to this project is to explore other datasets on crop drought damage.

The configuration of the CNN in this research has also seen limited attention. In the future, model architecture and hyperparameters could be optimized in order to improve the model's performance.

As discussed in the limitations, many improvements are possible regarding heuristics. The implemented heuristic was shown to improve the model's predictive capabilities to an extent, yet the implementation method is simplistic and has potential for improvement. This can be achieved firstly by exploring proper parameters for the bounds of pixel color. In this study, it opted to choose reasonable colors instead of performing such an analysis due to time constraints. Furthermore, the discoloration heuristic could be implemented differently by detecting clusters of yellow/brown pixels instead of masking singular pixels. Other heuristics, such as detecting crooked and fallen plants, could also be implemented to improve the model based on the survey results conducted in this study.

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A Questionnaire Visualizations

Here the distribution of answers for each image shown in the questionnaire is displayed.

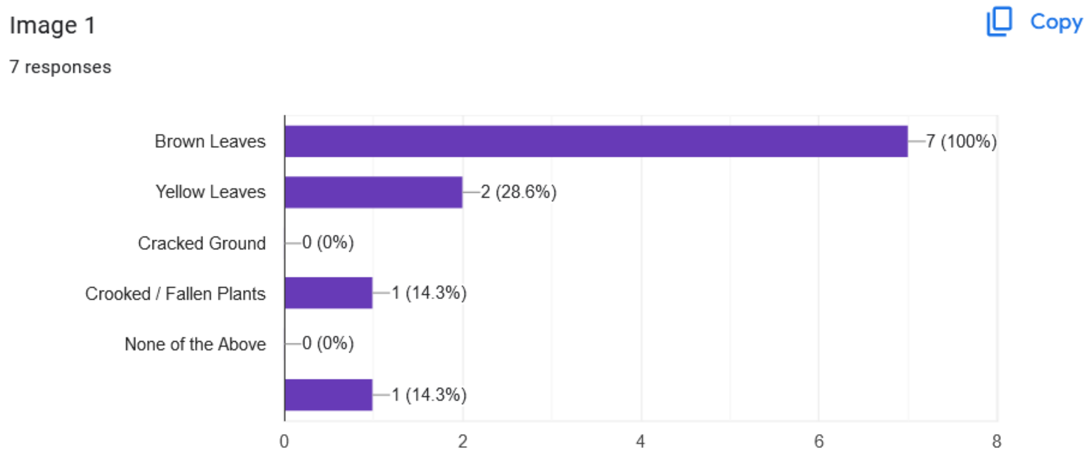

Figure 10: Questionnaire image 1 answer distribution

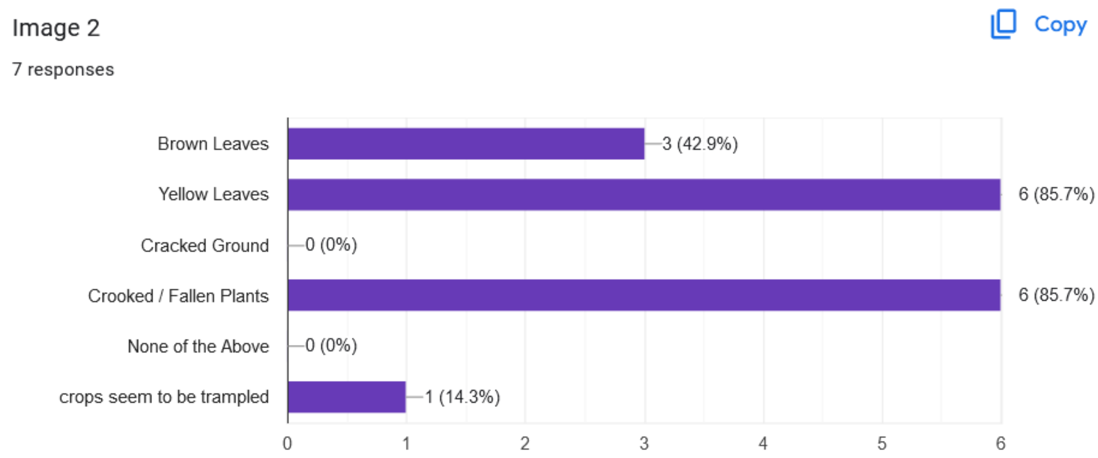

Figure 11: Questionnaire image 2 answer distribution

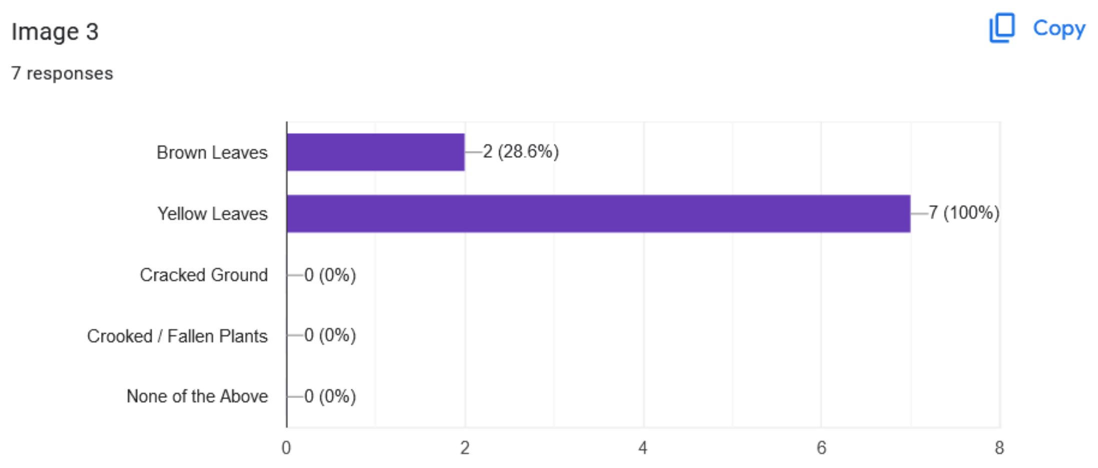

Figure 12: Questionnaire image 3 answer distribution

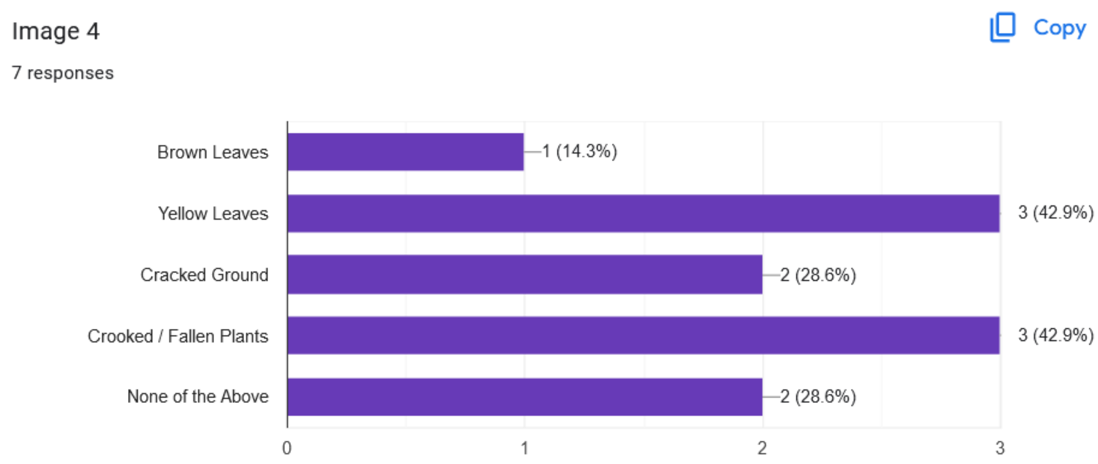

Figure 13: Questionnaire image 4 answer distribution

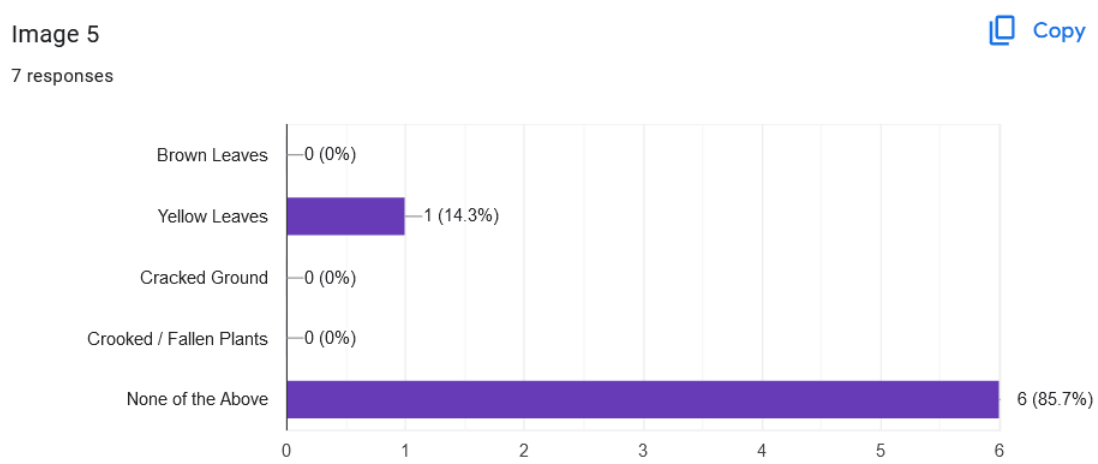

Figure 14: Questionnaire image 5 answer distribution

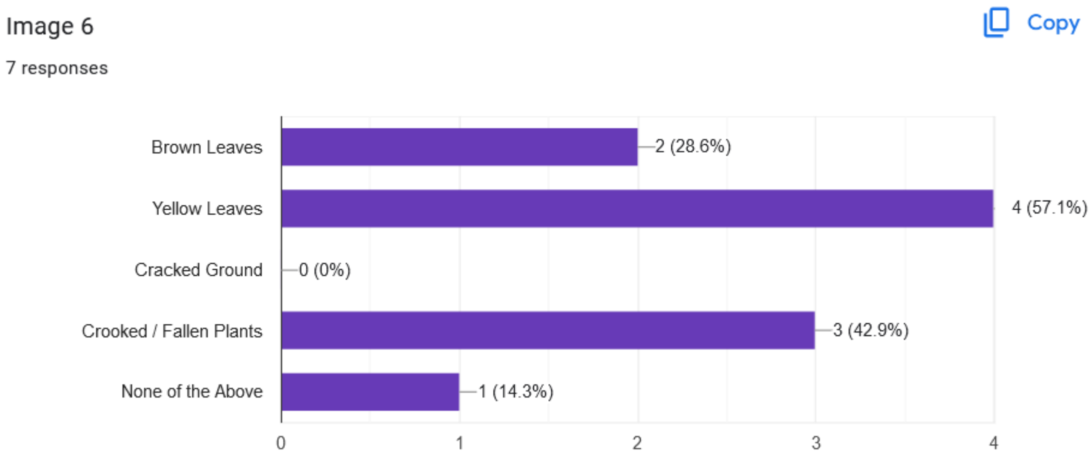

Figure 15: Questionnaire image 6 answer distribution

[scale=0.75]simages/questionnaire/q7.png

Figure 16: Questionnaire image 7 answer distribution

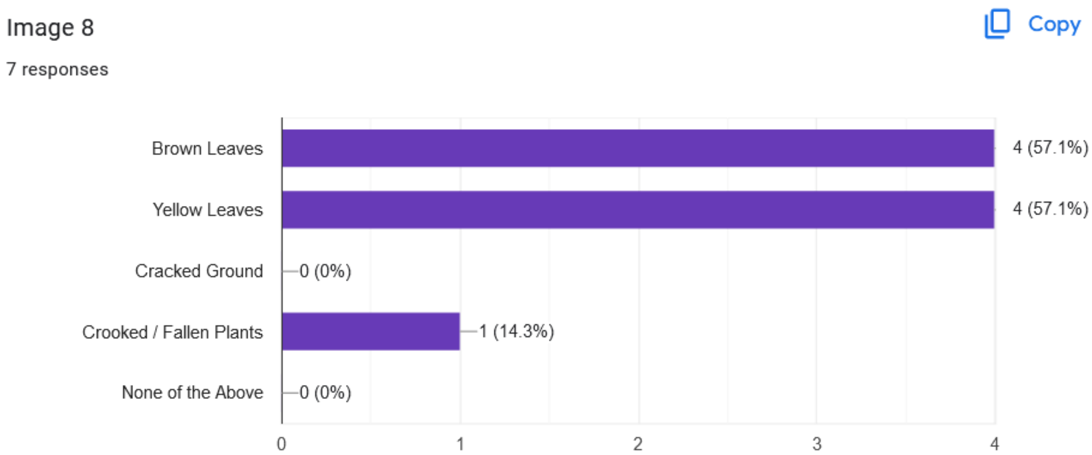

Figure 17: Questionnaire image 8 answer distribution

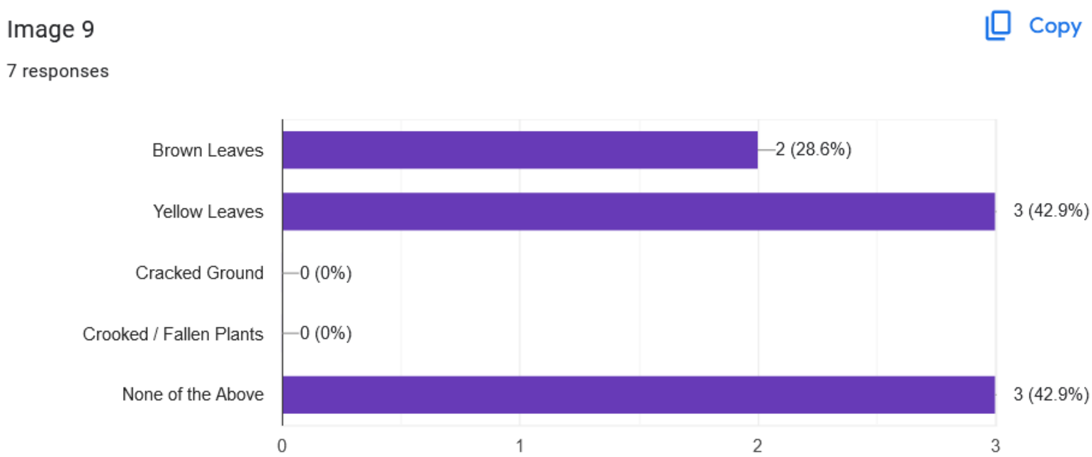

Figure 18: Questionnaire image 9 answer distribution

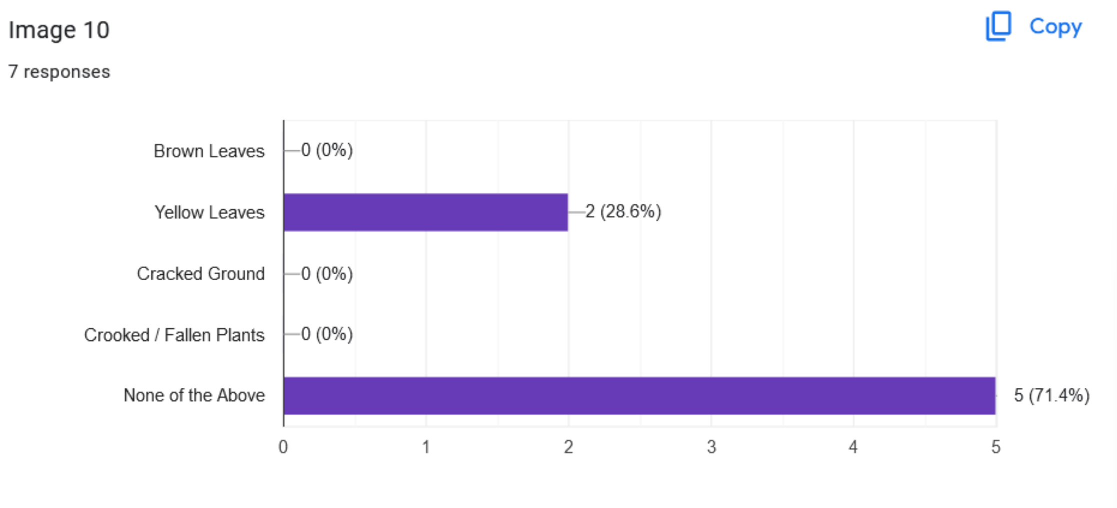

Figure 19: Questionnaire image 10 answer distribution

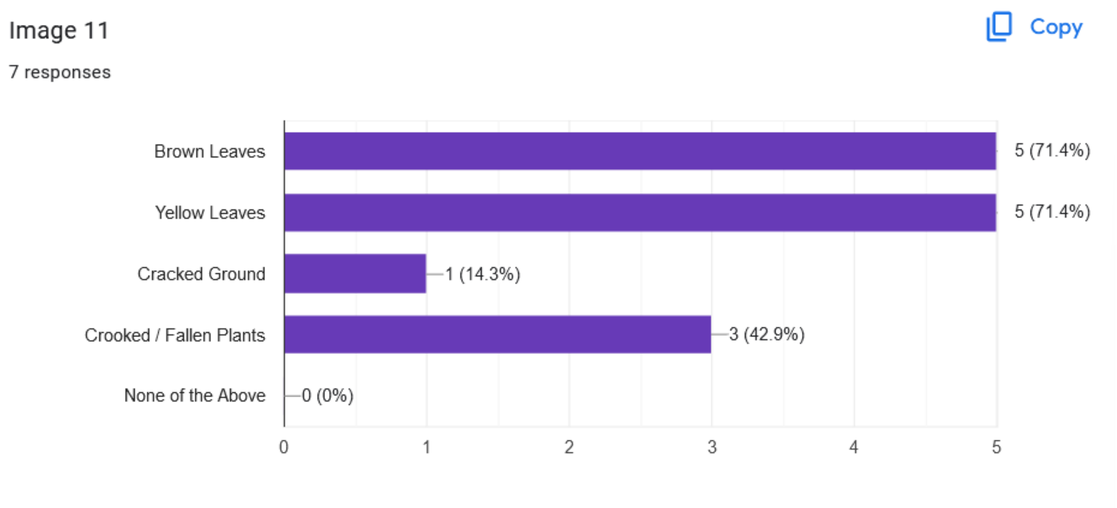

Figure 20: Questionnaire image 11 answer distribution

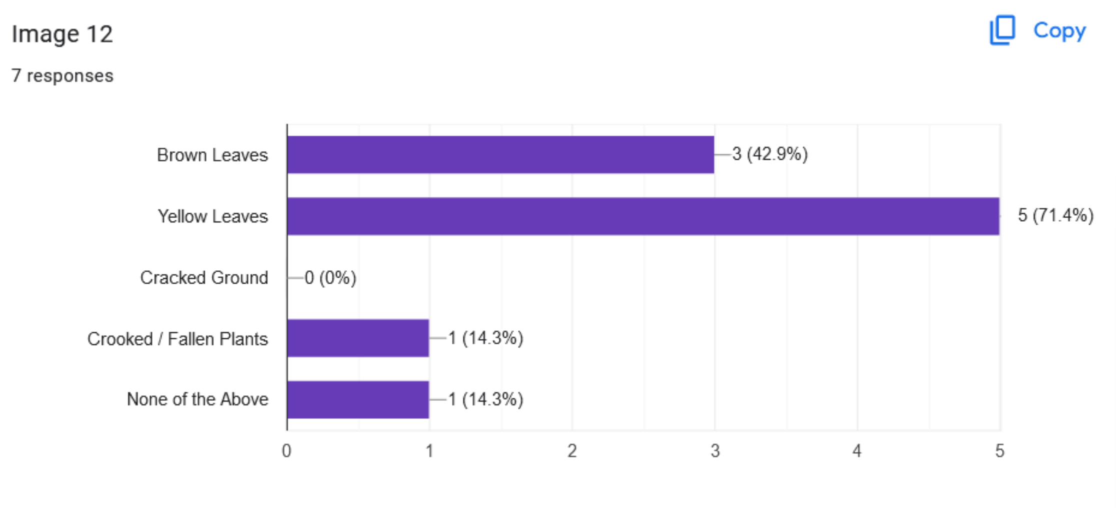

Figure 21: Questionnaire image 12 answer distribution

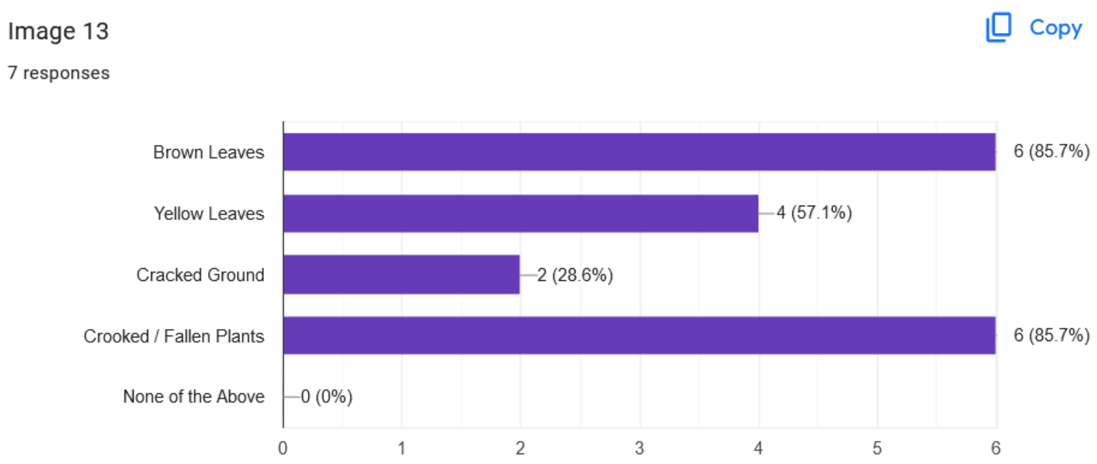

Figure 22: Questionnaire image 13 answer distribution

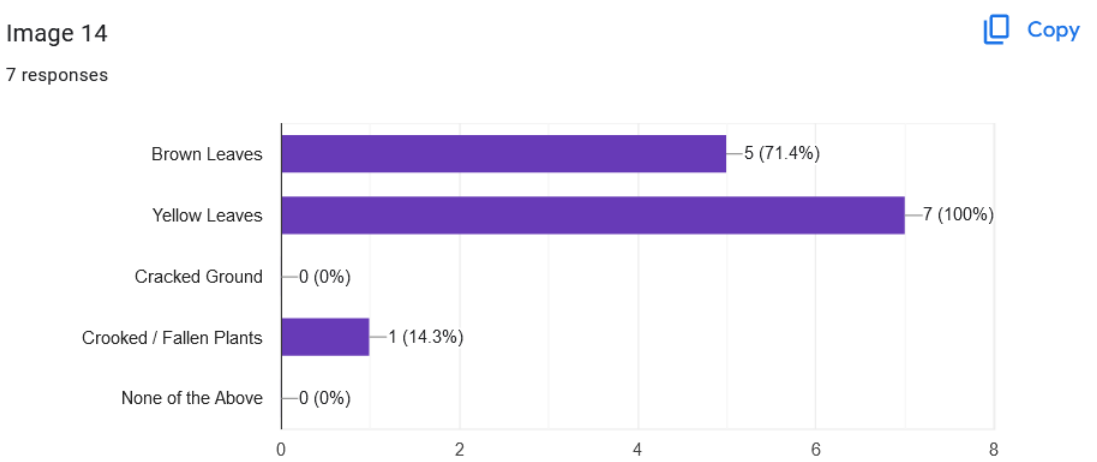

Figure 23: Questionnaire image 14 answer distribution

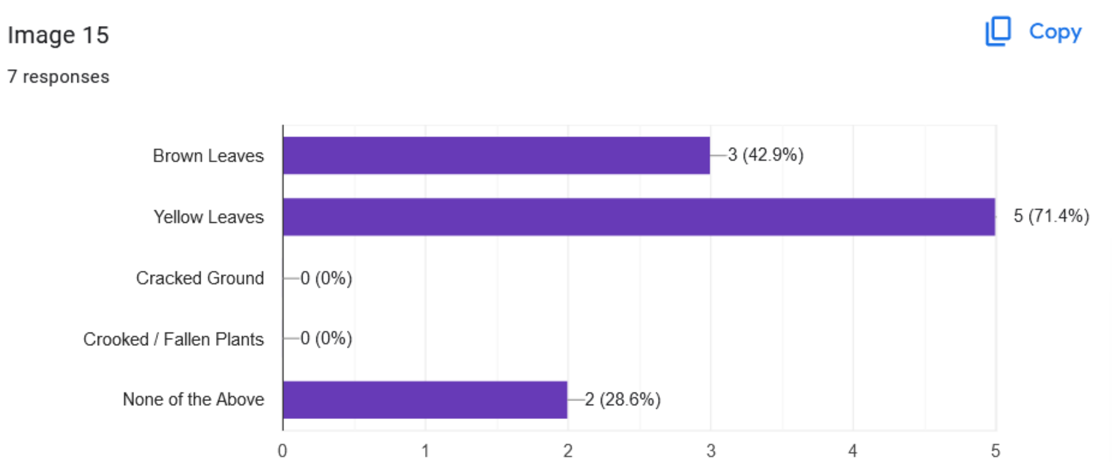

Figure 24: Questionnaire image 15 answer distribution

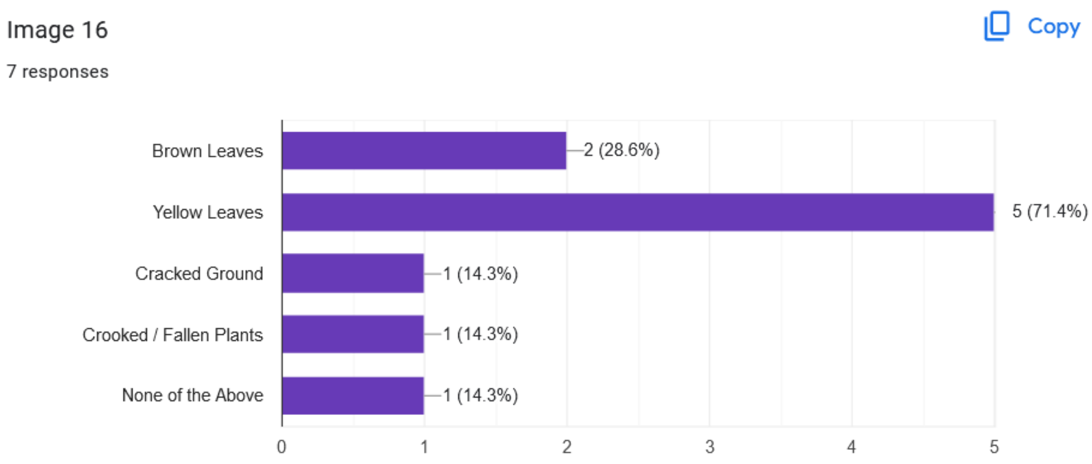

Figure 25: Questionnaire image 16 answer distribution

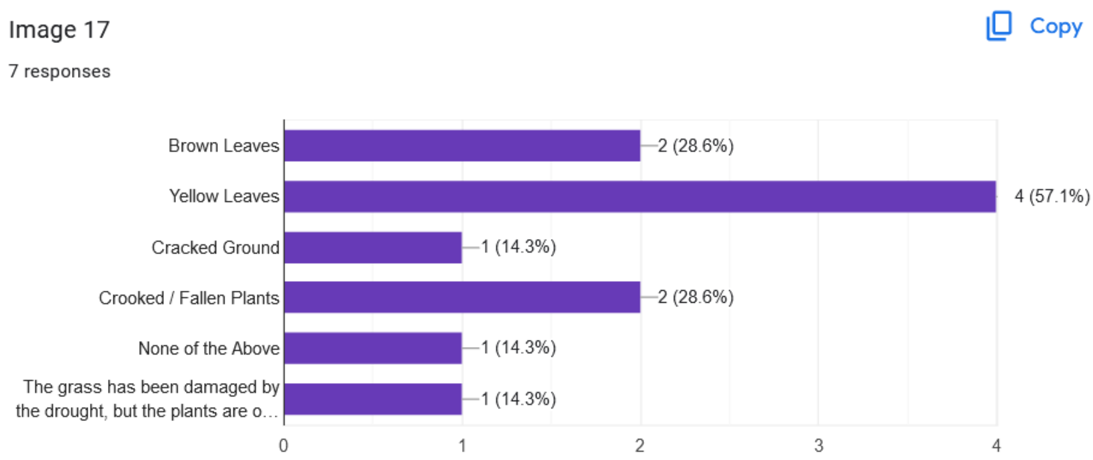

Figure 26: Questionnaire image 17 answer distribution

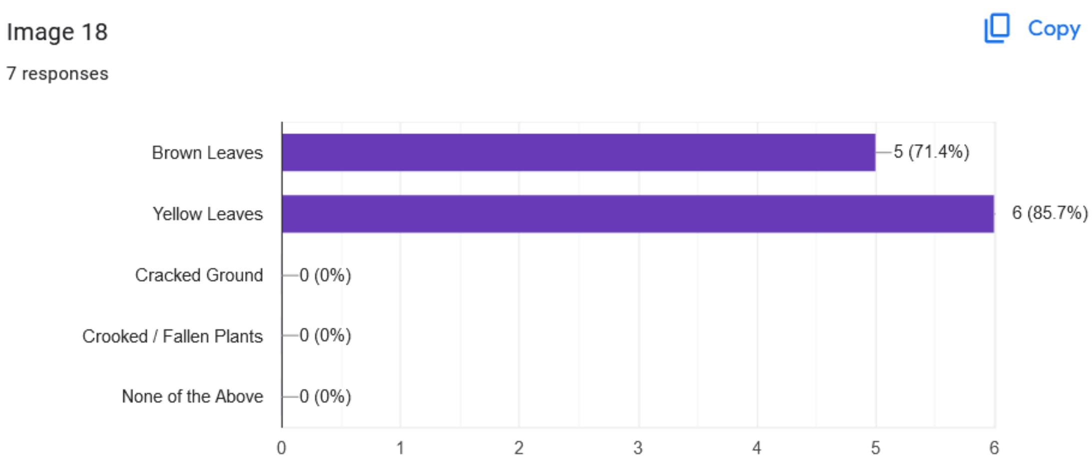

Figure 27: Questionnaire image 18 answer distribution

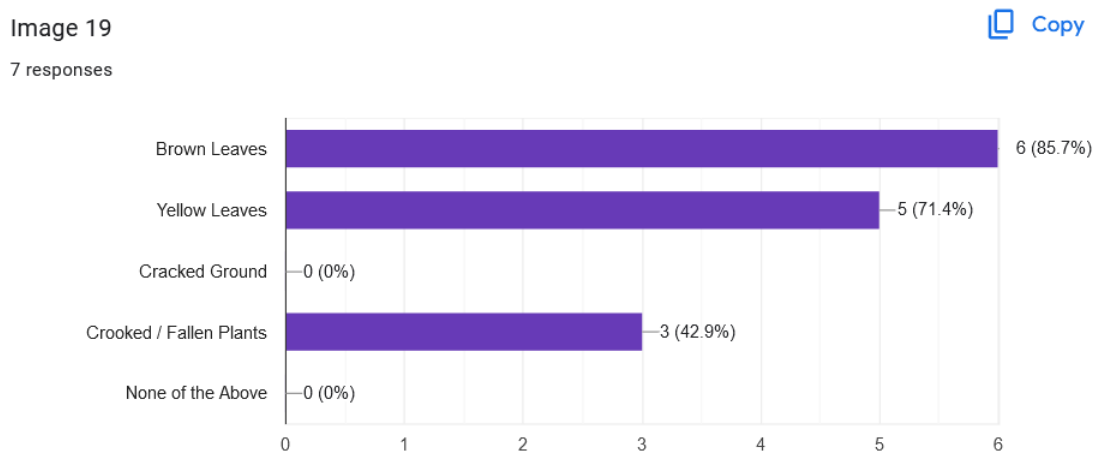

Figure 28: Questionnaire image 19 answer distribution

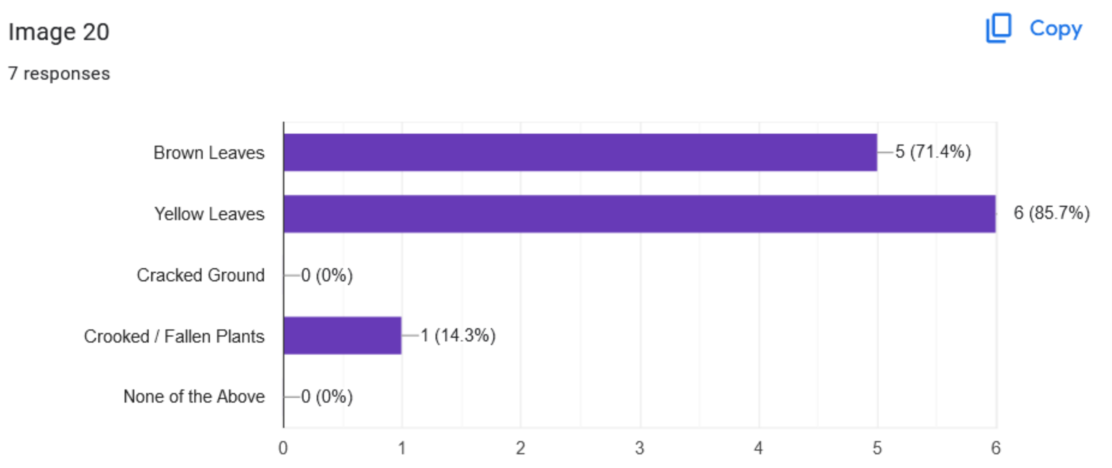

Figure 29: Questionnaire image 20 answer distribution